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Original Article

Integrating absolute distances in collaborative representation for robust image classification

Shaoning Zeng [a,*], Xiong Yang [a], Jianping Gou [b], Jiajun Wen [c]

[a] *Department of Computer Science, Huizhou University, 46 Yanda Road, Huizhou, Guangdong, China*
[b] *College of Computer Science and Communication Engineering, Jiangsu University, 301 Xuefu Road, Zhenjiang, Jiangsu, China*
[c] *Institute of Textiles and Clothing, Hong Kong Polytechnic University, Room QT715, Q Core, 7/F, Hong Kong*

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Abstract

Conventional sparse representation based classification (SRC) represents a test sample with the coefficient solved by each training sample in all classes. As a special version and improvement to SRC, collaborative representation based classification (CRC) obtains representation with the contribution from all training samples and produces more promising results on facial image classification. In the solutions of representation coefficients, CRC considers original value of contributions from all samples. However, one prevalent practice in such kind of distance-based methods is to consider only absolute value of the distance rather than both positive and negative values. In this paper, we propose an novel method to improve collaborative representation based classification, which integrates an absolute distance vector into the residuals solved by collaborative representation. And we named it AbsCRC. The key step in AbsCRC method is to use factors a and b as weight to combine CRC residuals res_{crc} with absolute distance vector dis_{abs} and generate a new deviation $r = a \cdot res_{crc} - b \cdot dis_{abs}$, which is in turn used to perform classification. Because the two residuals have opposite effect in classification, the method uses a subtraction operation to perform fusion. We conducted extensive experiments to evaluate our method for image classification with different instantiations. The experimental results indicated that it produced a more promising result of classification on both facial and non-facial images than original CRC method.

Keywords: Sparse representation; Collaborative representation; Integration; Image classification; Face recognition

1. Introduction

Image classification is an crucial technique applied in biometrics like face recognition [1,2] and one of the most significant steps in image classification is to represent or code the images. Proper description or representation of images is the basis of achieving robust image classification results [3,4]. Only with well represented, one subject in the form of the image can be easily distinguished from the others. The basic process of representation-based classification is firstly representing the targeted sample with a linear combination on training samples and then evaluating the dissimilarity to classify the test sample into a closest class. Representation-based classification algorithms play a significant role in face recognition. Among various representation-based classification methods [5—7], sparse representation (SR) and collaborative representation (CR) based classifications are two of most crucial methods that have drawn wide attention [8,9].

Despite face recognition is a convenient biometric technology and has been widely studied, there is still lots of challenge in this area. First, face images may be captured in severe variation of poses, illuminations and facial expressions. Consequently, even the images of one same face may differ significantly, which is likely to corrupt the discrimination. Furthermore, it is another big problem that lack of enough

* Corresponding author.
E-mail addresses: zxn@outlook.com (S. Zeng), xyang.2010@hzu.edu.cn (X. Yang), goujianping@ujs.edu.cn (J. Gou), jiajun.wen@polyu.edu.hk (J. Wen).
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training samples for robust face recognition. Some researchers proposed various methods to create more representations of one face to improve the accuracy of face recognition. Gao et al. proposed a virtual face image generation for robust face recognition [10], and Thian et al. also proposed using visual virtual samples to improve face authentication [11]. Recently, Xu et al. proposed to reprocess images with symmetrical samples in sparse representation based image classification [12]. The combination of multiple methods of image classifications is effective for improving the classification accuracy [13]. How to obtain competitive and complementary contributions among multiple descriptions of images is an hot topic. Furthermore, even sparse representation and collaborative representation can be combined together for classification [14]. So integrating multiple classifiers is an effective approach to pursue robust image classification.

This paper proposes a novel method to integrate an absolute distance vector with the coefficient solved by CRC to improve image classification. The basic idea of our proposed method is to calculate an absolute distance vector between the query sample and the training samples when solving the collaborative coefficient, and then integrate the absolute distance vector dis_{abs} for the query sample with the collaborative residuals res_{crc} solved by CRC, with a pair of tuned fusion factors a and b. Therefore a new fusion residuals can be obtained with $r = a \cdot r_{crc} - b \cdot d_{abs}$, which is finally used to perform classification. We tested the proposed method on a number of facial or non-facial datasets and found that it archived higher accuracy than conventional CRC. The paper has the following main contributions to image classification. First, it proposes a novel fusion method to improve CRC. Second, it analyzes and implements a reverse integration on multiple classifiers. Third, it demonstrates an experiment way to find tuned factors for integration on multiple classifiers.

The structure of the following content in this paper is as follows. The related work on SRC, CRC is introduced in Section 2. In Section 3, we describe our proposed method to integrate absolute distances in collaborative representation based classification (AbsCRC). In the next Section 4, we analyze the selection of fusion factors a and b, as well as some classification examples in the experiments. Section 5 conducts our experiments on a couple of popular benchmark datasets, and Section 6 concludes the paper.

2. Related work

Our work is to improve CRC with a novel fusion method. CRC is proposed as an improvement to SRC, therefore we first analyze the work related with conventional SRC before digging into CRC.

2.1. Sparse representation based classification

Sparse representation based classification (SRC) algorithm was proposed by J. Wright et al. [8]. The basic procedure to perform classification based on sparse representation involves two steps, which are first representing the test sample with a linear combination on all training samples and then identifying the closest class based on the minimal deviation.

Assume that there are C subjects or pattern classes with N training samples $x_1, x_2, \ldots, x_n$ and the test sample is y. Let matrix $X_i = [x_{i,1}, x_{i,2}, \ldots, x_{i,n_i}] \in I^{m \times n_i}$ denote n_i training samples from the ith class. By stacking all columns from the vector of a $w \times h$ gray-scale image, we can obtain the vector to identify this image: $x \in I^m (m = w \times h)$. Each column of A_i is then representing the training images of the ith subject. So any test sample $y \in I^m$ from the same class can be denoted by a linear formula as:

$$y = a_{i,1}x_{i,1} + a_{i,2}x_{i,2} + \cdots + a_{i,n}x_{i,n}, \tag{1}$$

where $a_{i,j} \in I, j = 1, 2, \ldots, n_i$.

And then N training samples of C subjects can be denoted by a new matrix: $X = [X_i, X_2, \ldots, X_C]$. So (1) can be rewritten to a simpler form like:

$$y = X \cdot \alpha \in I^m, \tag{2}$$

where $\alpha = [0, \ldots, 0, a_{i,1}, a_{i,2}, \ldots c, 0, \ldots, 0]^T$ is the sparse coefficient vector in which only entries related with the ith class are not zero. This vector of coefficient is the key factor to affect the robustness of classification. It's noted that SRC using the entire training samples to solve the coefficient.

Next step in SRC is to perform an l_1-norm minimization to solve the optimization problem to pursue the sparsest solution to (2). And this result is used to identify the class of the test sample y. Here we use:

$$(\widehat{\alpha}) = \mathbf{arg\ min}_{\alpha} \|\alpha\|_1, \tag{3}$$

Next, SRC computes the residuals with this representing coefficient vector associated with ith class, that is:

$$\mathbf{r}_{src}(y) = \|y - X_i \cdot \widehat{\alpha}_i\|_2. \tag{4}$$

And finally output the identity of y as:

$$\mathbf{identity}(y) = \mathbf{arg\ min}_i \{\mathbf{r}_{src,i}\}. \tag{5}$$

Some SRC algorithms are also implemented by l_0-norm, l_p-norm ($0 < p < 1$), or even l_2-norm minimization. Xu et al. [15] exploited the $l_{1/2}$-norm minimization to shrink the sparsity inside the representation coefficient matrix. Allen Y. Yang et al. proposed fast l_1-minimization algorithms called augmented lagrangian methods (ALM) for robust face recognition [16]. Furthermore, many researchers proposed different SRC implementation and improvement, such as kernel sparse representation proposed by Gao et al. [17], an algorithm by Yang and Zhang that using a Gabor occlusion dictionary to raise the computing performance during the process for face occlusion [18], l_1-graph for image classification by Cheng et al. [19], sparsity preserving projections by Qiao et al. [20], and a representation model by prototype together with variation for sparsity based face recognition [21]. Studies also show that the classification accuracy can be also improved by using virtual samples [12,22,23]. All of these are trying to improve the robustness of image classification for face recognition. And it's